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Abstract— **The global world is dependent and integrated with all the ecosystems. To survive in the race, we must need to know about the birds and their habitats and importance to the existence of the human race on earth. However, it is difficult to recognize several species of birds, animals, and so on. In this paper, we presented a methodology to recognize local birds of Bangladesh using transfer learning techniques. The whole research work has been done using transfer learning in six different CNN architecture namely DenseNet201, InceptionResNetV2, MobileNetV2, ResNet50, ResNet152V2, and Xception. As to defeat the lack of much image data, augmentation is performed on the collected image data too. All the models are trained by 2800 data images and tested by 700 data images. Among all the discussed models, MobileNetV2 model exhibits the best performance in terms of various indicators such as F1-score, precision, recall, and accuracy. The accuracy, precision, recall, and F1 Score of MobileNetV2 are 96.71%, 96.93%, 96.71%, 96.75%. Then a comparative analysis has been performed for this work among the approaches as well. The obtained result shows that the working method is optimal and efficient for recognizing local birds of Bangladesh.**

Keywords- Bird, Transfer Learning, Xception, DenseNet201, InceptionResNetV2, MobileNetV2, ResNet50, ResNet152V2.

I. INTRODUCTION

Today's world is debating the consequences of artificial intelligence and the part AI is going to perform in shaping our future [1]. Machine learning is fast becoming dependencies on which we can develop intelligent applications. Nowadays our environment has been changing day by day. With this rapidly changing every day, new species of birds, animals, and trees are recognized. Using a machine learning technique, we can easily recognize birds and their species. Several machine learning techniques could be deployed to recognize the local birds of Bangladesh. Each of the algorithms is domain-specific. Since a huge number of machine learning algorithms gained popularity for developing intelligent applications, we need to investigate those with the test data set to see which one is given the best accuracy [2]. In Bangladesh, approximately 814 species of birds are living [3]. It is difficult to recognize all those birds manually but using machine learning and neural networks we can recognize them easily. We are here concentrating to recognize seven local birds namely the Red-vented Bulbul, House Sparrow, Crow, Magpie, Common kingfisher, Myna, and Cuckoo species of Bangladesh. To reduce image classification constraints, we can use the transfer learning technique to compose an accurate data model [4].

In this paper, we recognized local birds of Bangladesh and then compared particular pre-eminent procedures in the circumstances of local bird recognition, and the approaches are done based on machine learning. The elementary purpose of this research is to use transfer learning to recognize local birds of Bangladesh. In the whole research work, we implement the approaches namely DenseNet201, InceptionResNetV2, MobileNetV2, ResNet50, ResNet152V2, and Xception. Moreover, MobileNetV2 is lightweight CNN (Convolutional Neural Network) architecture and in comparison, all the applied approaches of MobileNetV2 and Xception both give the best accuracy of 96.71%. After calculating the accuracy, we differentiate them by calculating several evaluation metrics.

The structure of this research paper is as regards: Section II presents the relevant study to find the research gap among the existing research; Section III presents the methodology with the process of recognition; Section IV illustrates the obtained result of this work with details discussion of achieved results. Lastly, Section V concludes the research with the direction of forthcoming research.

II. RELATED WORK

The transfer learning technique has been applied for the recognition and classification of numerous objects in enormous research. But there is a little work on local bird's recognition adopting this technique. Some exertion has been implemented for recognizing numerous objects using transfer learning.

A. Jaiswal et al [5] developed a system for classifying patients of Covid-19 infected. They apply the Transfer learning based DenseNet-201 model for classifying the patients and the

ImageNet model for extracting features from the image of a CT scan. Total 2492 image of CT scan from data source SARS-Cov-2 has been demeanor for training purposes and their obtained accuracy is 97.4%. X. Wan et al [6] presented an approach for recognizing age based on the face in deep learning. For extracting facial features and recognizing the face, Inception-Resnet V2 model has been applied. The size of the dataset for training the model has not alluded here along with the improvement obtained accuracy. Transfer learning-based inception ResNet-V2 model for breast cancer classification approach was presented by C.A. Ferreira et al [7]. Exploiting feature extracting layer, the training of top layers and fine-tuning has been performed. They have not alluded any data size for training and exploiting data has been segmented. The acquired accuracy for this approach is 76% on blind test sets. J. Liu and X. Wang [8] developed a system for recognizing tomato disease named gray leaf spot applying MobileNet-V2 and YOLO-V3 models. For real-time classification of this disease, the tomato grower needs to install the app. The explicit training data set has not been alluded here. Their obtained accuracy is based on the structure of captured images and the size of captured images influences the speed of detection. Q. Xiang et al [9] presented a technique for classifying fruit images. They applied the transfer learning-based MobileNet-V2 model for extracting features of the images and softmax classifier for the classification of features. 3670 images of 5 categories fruits have been exploited for training and their obtained accuracy for classifying fruits is 85.12%. L. Hu and Q. Ge [10] developed a system for recognizing facial expression by applying the transfer learning-based MobileNet-V2 model. Three types of databases relating to facial expression named CK+, JAFFE, and FER2013 are utilized for improved accuracy. The Faceboxes algorithm is used here for detecting the face box of the process image. Their obtained accuracy is 97.98%. M. A. Al-antari et al [11] developed an automatic system for recognizing injury to the skin utilizing dermoscopy images. Adopting numerous classification models namely DenseNet201, Inception-V3, InceptionResNet-V2 and ResNet-50, this recognition system has been trained. Seven classes of the image in skin lesions are utilized here. The accuracy of ResNet-50 outperforms other model's accuracy. L. V. Fulton et al [12] presented a technique for classifying Alzheimer's disease by applying the Boosted machine and ResNet-50 models. Three categories of data named clinical, socio-demographic, and MRI are exercised here for predicting the classification of diseases. Gradient Boosted machine is used for presenting Alzheimer's disease based on numerous symptoms and ResNet-50 for presenting the rating of clinical dementia. They used a total of 4139 images and obtained 98.99% accuracy. M. T. Habib et al [13] performed comparison among the classifiers to recognize the papaya disease. Among all the classifiers, SVM outperformed than others with achieving more than 95.00% accuracy and KNN performed worst with achieving the accuracy 71.11%. Recognition of rose flower disease by applying MobileNet model for two different way namely transfer learning and without transfer learning techniques is presented by A. Rajbongshi et al [14]. They obtained the highest accuracy for transfer learning technique that is 95.63%. M. M. Rahman et al [15] worked with the recognition of local birds applying MobileNet and Inception-v3 models in two different ways. One is using transfer learning and another is without transfer learning. Seven classes of local birds have been utilized here. Their obtained test accuracy is 91.00% which has been accomplished by adopting MobileNet with transfer learning.

III. METHODOLOGY

The following Fig. 1 shows the working procedure of local bird recognition using transfer learning. Before training the transfer learning model, raw data needs to be processed. In the data processing step, data augmentation, labeling, and resizing are performed due to some reasons such as data augmentation help to enhance the dataset size. The six CNN models are trained here using these processed data based on the transfer learning techniques. The testing of the trained models is performed to examine the performance. Lastly, we have found the best models for transfer learning in this context by analyzing the several evaluation metrics.

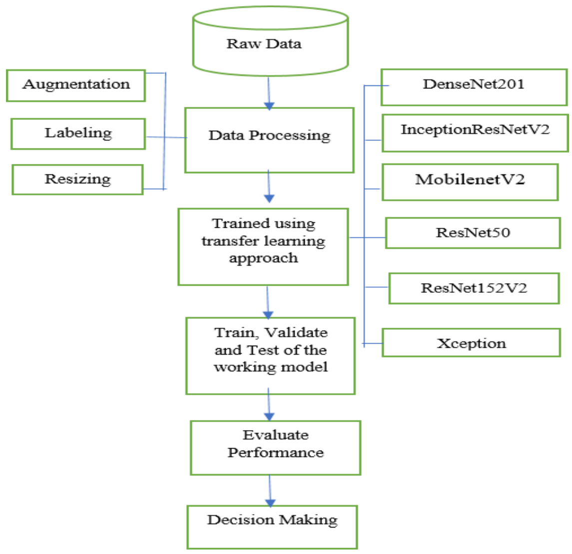


Figure 1. Local Bird Recognition Procedure using Transfer Learning.

A. *Dataset Description*

First, we have collected 100 images of each bird class. We have worked on seven bird's species of Bangladesh here. We have created 500 images data for each of the classes by performing the augmentation techniques on the collected data. So, after this, we have a total of 3500 data for seven classes. Among these data, we have used 400*7=2800 data for training purposes and 100*7=700 data for testing purposes. A portion of the bird's dataset with their name and pictorial representation is tabulated in the TABLE I.

B. *Model Description*

The CNN is a well-known ANN that is used to do image recognition and classifications widely. Convolutional Neural

Network requires much lower pre-processing as compared to other traditional classification algorithms. A CNN consists of different layers namely the input layer, convolution layer, pooling layer, fully connected layer, output layer. The above-mentioned different layers can be used repeatedly to form a deep CNN architecture.

The first layer of every convolutional neural network is the input layer and this layer retains the image's raw pixel value. The feature is a vital and unique property of an image. In the Convolution layer, features are extracted from an input image, and this layer is considered as a major building block. In this layer, different kernels or filters are used here. Convolution of an image with different filters or kernels can execute several operations such as edge detection, sharpening, and blur of the image. The main objective of the Convolution operation is to extract out several high-level features. In the convolution layer, a matrix multiplication operation between the filter and the portion of the image takes place which the kernel is hovering. The filter will be moving to the right with a fixed stride value until it parses the comprehensive width. Passing on, it goes down to the commencement (left side) of the image with the same stride value and it iterates till the whole image is crossed. The number of pixels shifted over the input matrix is known as stride. In CNN, to overcome the problem of shrinking outputs and also losing information on corners of the image after convolution operations, padding can be used with an input image. The next layer is the Pooling layer which helps to diminish the number of parameters when the images are too big. Spatial pooling is also known as downsampling or subsampling which diminish the dimensionality of each map but keeps vital information. It can be of different types namely Max, Average, and Sum Pooling. Among these three techniques, Max pooling takes the most substantial element from the rectified feature map. Average pooling is taking the average value of the elements. Sum pooling is the summation of all elements in the feature map. Each neuron is connected to every neuron in the previous layer in a FC layer and each connection contains its weight. This Fully connected layer (FC) mainly flattens the input feature representation into a feature vector. This layer performs the function of high-level reasoning. The output layer is the final layer of the CNN and is capable for producing the output probability of each of the given input classes. A softmax unit is commonly used here to obtain the output probability because it generates a well-performed probability distribution.

There are various CNNs architectures available and we have used transfer learning concepts in six CNN architecture namely DenseNet201, InceptionResNetV2, MobileNetV2, ResNet50, ResNet152V2, and Xception to recognize the local birds. The enhancement of learning in a new task through the transfer of knowledge from a relevant task that has already been learned is known as transfer learning [16]. But in transfer learning approaches [17], the tasks can be different but their domains should be the same. So, this is not possible to apply transfer learning between image classification and speech recognition as the input datasets are different types for the two tasks.

Since our working dataset is scanty as contrasted to the imagenet dataset, it is not a good idea to fine-tune the CNN due to the chance of overfitting. Hence, we removed the top layer of the pre-trained base CNN. After this, we added a FC layer with some dropout and the output layer that matches the number of classes (seven classes) in the working dataset. Then we randomized the weights of the new FC layer and made all the weights trainable of the pre-trained network. Lastly, to update the weights of the new FC layers, training of the network is performed.

C. Experiments

We have trained the models with 100 epochs and batch size is 8. Here, we have used 'rmsprop' as the optimizer, 'categorical_crossentropy' as the loss function with the initial learning rate 0.001 to train and test the models. We used Nvidia Geforce 2080 Super GPU with 8GB memory to do this task.

D. Performance Evaluation

Performance evaluation metrics measurement is essential to examine the model's performance. To do this, we have computed several performance evaluation metrics. To compute the above-mentioned metrics, we have used the following mathematical formula (1) to (4).

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \qquad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (2)$$

TABLE I. BIRD'S DATASET WITH THEIR NAME AND PICTORIAL REPRESENTATION

English Name	Red-vented bulbul	House Sparrow	Crow	Magpie	Common kingfisher	Myna	Cuckoo
Scientific Name	*Pycnonotus cafer*	*Passer domesticus*	*Corvus corax*	*Copsychus saularis*	*Alcedo atthis*	*Acridotheres tristis*	*Cuculus canorus*
Image Representation							

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1-Score} = 2 \times \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (4)$$

IV. RESULT AND EXPERIMENTAL ANALYSIS

The overall result of the evaluation metrics is presented in TABLE II. MobileNetV2 and Xception both transfer learning approaches attained the highest accuracy 96.71%. But when we looked into the precision, and F1 score, we found that MobileNetV2 achieved 96.93% and 96.75% respectively. But when we looked into the recall, we found that MobileNetV2 and Xception achieved the equivalent result of 96.71%. So, we found that overall MobileNetV2 outperformed other learning techniques.

TABLE III presents class wise precision for all the applied transfer learning techniques. For the class Red-vented bulbul, MobileNetV2 and Xception attained 100.00% which is the highest precision among all. For the class House Sparrow, MobileNetV2 achieved 98.02% which is highest among all. For the class Crow, InceptionResNetV2 achieved 93.46% which is the highest among all. For the class Magpie, ResNet152V2 achieved the highest precision and it is 100.00%. For the class Common kingfisher, DenseNet201, ResNet50, and Xception achieved the highest and it is 100.00%. For the class Myna, MobileNetV2 achieved 98.95% which is highest among all. For the class Cuckoo, Xception achieved the highest precision which is 96.12%.

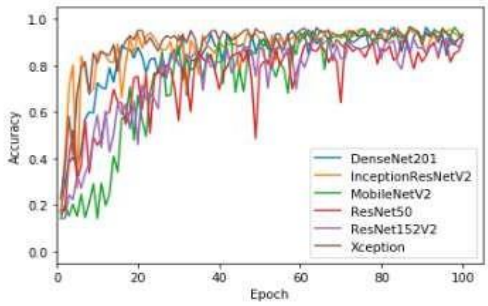
TABLE IV presents class wise recall for all the applied transfer learning techniques. For the class Red-vented bulbul, DenseNet201 and InceptionResNetV2 attained 98.00% which is the highest recall among all. For the class House Sparrow, MobileNetV2 achieved 99.00% which is highest among all. For the class Crow, InceptionResNetV2 and Xception achieved 100.00% which is the highest among all. For the class Magpie, Xception achieved the highest result and it is 99.00%. For the class Common kingfisher, DenseNet201 achieved the highest recall and it is 99.00%. For the class Myna, MobileNetV2 achieved 94.00% which is highest among all. For the class Cuckoo, Xception achieved the highest recall which is 99.00%.

TABLE V presents the class-wise F1 Score for all the applied transfer learning techniques. For the class Red-vented bulbul, DenseNet201 and InceptionResNetV2 attained 98.00% which is the highest F1 score among all. For the class House Sparrow, MobileNetV2 achieved 98.51% which is highest among all. For the class Crow, InceptionResNetV2 achieved 96.62% which is the highest among all. For the class Magpie, Xception achieved the highest result and it is 98.51%. For the class Common kingfisher, DenseNet201 achieved the highest recall and it is 99.50%. For the class Myna, MobileNetV2 achieved 96.41% which is highest among all. For the class Cuckoo, Xception achieved the highest recall which is 97.54%.

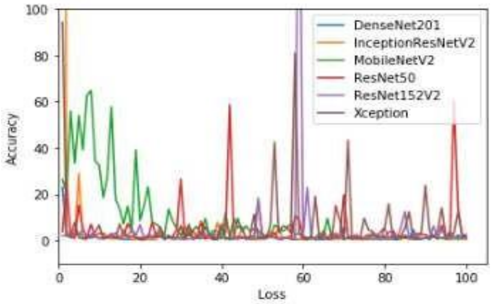
Fig. 2(a) represents the accuracy over the epochs and Fig. 2(b) represents the loss over the epochs. The different colors are used to represent the accuracy and loss of different models. The basic behavior of the accuracy and loss of a good model is the accuracy will increase over time and loss will decrease over time. From Fig.2, it is observed that the accuracy of the applied techniques increases over time where loss decreases over time though there are some fluctuations in the loss curve diagram.

We have also plotted the ROC curve observe the quality of a model's output. As it is a multi-class (seven class) problem, we have presented both the Macro Average Roc Curve and Micro Average Roc Curve at Fig. 3. Fig. 3(a) presents the Macro Average ROC Curve and Fig. 3(b) presents the Micro Average ROC Curve. In this work, the variation between Macro and Micro Average ROC Curve is little. From Fig. 3, we observed the AUC is large enough for both Macro and Micro Average ROC Curve. So, we can say all the working models have performed well enough, as the larger AUC is usually better.

From Fig. 3, we can see that the ROC of all models has larger AUC which indicates that all the working techniques are working better here. But from the above represented table, we found the best working approach for overall and individual scenarios as in table we presented the result comparison in numerical format for all the working approaches.



a. Accuracy of different techniques over the epochs.



b. Loss of different techniques over the epochs.

Figure 2. Accuracy and loss of different techniques over the epochs.

TABLE II. EXPERIMENTAL RESULT OF APPLIED TRANSFER LEARNING TECHNIQUES

Model Metric	DenseNet201	InceptionResNetV2	MobileNetV2	ResNet50	ResNet152V2	Xception
Accuracy	96.43%	96.14%	96.71%	90.71%	91.71%	96.71%
Precision	96.52%	96.20%	96.93%	90.85%	92.16%	96.84%
Recall	96.43%	96.14%	96.71%	90.71%	91.71%	96.71%
F1 Score	96.44%	96.14%	96.75%	90.75%	91.76%	96.72%

TABLE III. CLASS WISE PRECISION FOR APPLIED TRANSFER LEARNING TECHNIQUES

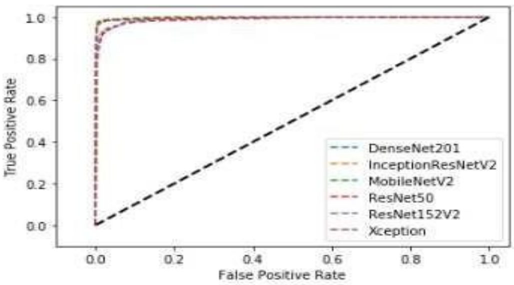
Class	DenseNet201	InceptionResNetV2	MobileNetV2	ResNet50	ResNet152V2	Xception
Red-vented bulbul	98.00%	98.00%	100.00%	88.46%	95.70%	100.00%
House Sparrow	96.94%	93.14%	98.02%	86.79%	88.99%	95.96%
Crow	89.91%	93.46%	87.50%	88.24%	85.59%	90.91%
Magpie	98.98%	98.96%	98.97%	96.84%	100.00%	98.02%
Common kingfisher	100.00%	97.03%	98.99%	100.00%	98.94%	100.00%
Myna	95.83%	96.84%	98.95%	90.91%	93.18%	96.88%
Cuckoo	96.00%	95.96%	96.08%	84.69%	82.73%	96.12%

TABLE IV. CLASS WISE RECALL FOR APPLIED TRANSFER LEARNING TECHNIQUE

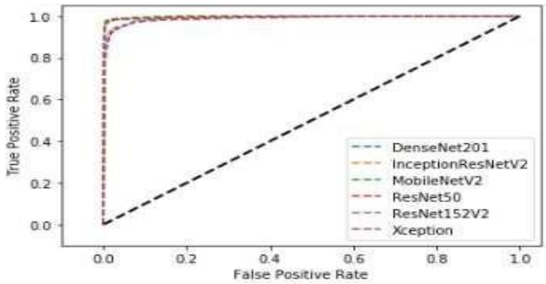
Class	DenseNet201	InceptionResNetV2	MobileNetV2	ResNet50	ResNet152V2	Xception
Red-vented bulbul	98.00%	98.00%	94.00%	92.00%	89.00%	96.00%
House Sparrow	95.00%	95.00%	99.00%	92.00%	97.00%	95.00%
Crow	98.00%	100.00%	98.00%	90.00%	95.00%	100.00%
Magpie	97.00%	95.00%	96.00%	92.00%	95.00%	99.00%
Common kingfisher	99.00%	98.00%	98.00%	96.00%	93.00%	95.00%
Myna	92.00%	92.00%	94.00%	90.00%	82.00%	93.00%
Cuckoo	96.00%	95.00%	98.00%	83.00%	91.00%	99.00%

TABLE V. CLASS WISE F1-SCORE FOR APPLIED TRANSFER LEARNING TECHNIQUES

Class	DenseNet201	InceptionResNetV2	MobileNetV2	ResNet50	ResNet152V2	Xception
Red-vented bulbul	98.00%	98.00%	96.91%	90.20%	92.23%	97.96%
House Sparrow	95.96%	94.06%	98.51%	89.32%	92.82%	95.48%
Crow	93.78%	96.62%	92.45%	89.11%	90.05%	95.24%
Magpie	97.98%	96.94%	97.46%	94.36%	97.44%	98.51%
Common kingfisher	99.50%	97.51%	98.49%	97.96%	95.88%	97.44%
Myna	93.88%	94.36%	96.41%	90.45%	87.23%	94.90%
Cuckoo	96.00%	95.48%	97.03%	83.84%	86.67%	97.54%



a. Macro Average ROC Curve.



b. Micro Average ROC Curve.

Figure 3. ROC Curve for different techniques. Conclusion and future work.

V. Conclusion and Future work

Here we have mainly worked on seven local birds namely the Red-vented Bulbul, House Sparrow, Crow, Magpie, Common kingfisher, Myna, and Cuckoo species of Bangladesh. To recognize the bird, we have applied six transfer learning techniques. In this work, 80% of data (2800 images) are used to train the model and the rest of the 20% data (700 images) are used to accomplish the work. After analyzing the evaluation metrics, we found that the transfer technology MobileNetV2 outperforms the other transfer learning approaches in terms of result of the evaluation metrics. From TABLE II, the accuracy, precision, recall, and F1 Score of MobileNetV2 are 96.71%, 96.93%, 96.71%, 96.75%. The class wise Precision, Recall, and F1 Score is also presented in the result sections by the rest of the table. In the future, we have planned to recognize the birds from the video data with large class dataset.

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